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The Effect of Time on EMG classification of hand motions in able-bodied and transradial amputees

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ABSTRACT

While several studies have demonstrated the short-term performance of pattern recognition systems, long-term investigations are very limited. In this study, we investigated changes in classification performance over time. Ten able-bodied individuals and six amputees took part in this study. EMG signals were recorded concurrently from surface and intramuscular electrodes, with intramuscular electrodes kept in the muscles for seven days. Seven hand motions were evaluated daily using linear discriminant analysis and the classification error quantified within (WCE) and between (BCE) days. BCE was computed for all possible combinations between the days. For all subjects, surface sEMG (7.2 ± 7.6%), iEMG (11.9 ± 9.1%) and cEMG (4.6 ± 4.8%) were significantly different ($P < 0.001$) from each other. A regression between WCE and days (1-7) was on average not significant implying that performance may be considered similar within each day. Regression between BCE and time difference (Df) in days was significant. The slope between BCE and Df (0-6) was significantly different from zero for sEMG (R^2=89 %) and iEMG (R^2=95%) in amputees. Results indicate that performance continuously degrades as the time difference between training and testing day increases. Furthermore, for iEMG, performance in amputees was directly proportional to the size of the residual limb.

Keywords: — Electromyography; Pattern recognition; Classification; Myoelectric control; multiday performance

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I. INTRODUCTION

Electromyography (EMG) has been widely used to extract a control signal in numerous human-machine interfaces. These interfaces have applications in clinical and rehabilitation medicine and have been studied extensively in the last two decades. EMG signals are stochastic in nature and measures of its amplitude can be used to estimate muscle activation level and force [Kamavuako et al, 2013]. EMG signals are one of the major neural control sources for myoelectric prostheses, providing quasi-natural control modalities although with limited functionalities.

Approximately 100 000 people in the USA have upper limb amputation, 57% of whom are transradial amputees [Ziegler-Graham et al, 2008; Esquenazi et al, 1996; Merrill et al, 2011]. Rejection rates for myoelectric prostheses are high [Atkin et al, 1996; Engdhal et al, 2015; Biddiss et al, 2007] due to their limited ability to provide good range of movement, highly coordinated movements, robustness over time, and intuitive control [Atkin et al, 1996; Kyberd et al,2011]. Myoelectric control can be grouped into two types: (1) conventional myoelectric control strategies (2) pattern recognition (PR) based myoelectric control strategies. Conventional control strategies are based on signal amplitude, and they have found widespread clinical application because of their simplicity and robustness. They are limited in their ability to control more than one to two degrees-of-freedom (DOF), as switching DOF requires a non-intuitive trigger, such as a muscle co-contraction.

PR-based control strategies have been studied extensively in the last two decades. These techniques are based on the expectation that a selected muscle generates repeatable EMG signals. These signals can be described by a set of features that will be different from one motion to another [Hargrove et al, 2008]. PR-based schemes have demonstrated the potential for controlling more DOFs than conventional control schemes. Although high accuracies (>95%) have been reported in the literature for multiple DOFs using various combinations of techniques in feature extraction, dimensionality reduction, and classification algorithms, this strategy is challenged by many issues including muscle fatigue, electrode shift, skin conductivity, and limb position [Scheme et al, 2010; Hargrove et al, 2010; Young et al, 2011]. These and other effects have led researchers and clinicians to qualitatively observe a degradation in performance in the time elapsed since training the classifier. Tkach et al. (2010) and Young et al. (2012) studied the effect of a shift in electrode positions and variation in force during contraction. It was reported that increasing the inter-electrode distance from two to four cm improved classification performance and controllability [Young et al, 2012]. Similarly selecting a stable EMG feature set can reduce the effect of electrode location shift and varying effort level on classification by 16% [Tkach et al, 2010]. [Fougner et al, 2011] studied the effect of limb positions on EMG pattern recognition. Results indicated that EMG classification accuracy is strongly dependent on limb position and it was recommended to develop a training strategy that accounts for multi-position use. Apart from these factors, classification errors due to real-world conditions such as changes in electrode-skin impedance, inter-electrode distance and subject dependent psychological changes greatly affect the performance in terms of classification and controllability [Scheme et al, 2010; Hargrove et al, 2010; Young et al, 2011]. While many studies focus on the challenges mentioned above, the effect of time on the classification of hand motions has received less attention in the literature. The need for long-term studies is justified due to the indication of variations in the EMG signals over time [Kaufmann et al, 2010].

Phinyomark et al. (2013) investigated the behaviour of fifty time and frequency domain features for ten motions using EMG data recorded for 21 days on a single able-bodied Subject. Results showed that the sample entropy feature outperforms other features in robustness and accuracy including root mean square, the fourth order cepstrum coefficients and waveform length. He et al. (2015) investigated the changes in EMG classification performance over 11 consecutive days in eight able-bodied subjects and two amputees. It was observed that, when the classifier was trained on data from one day and tested on data in the following days, the classification decreased exponentially but plateaued after four days for able-bodied subjects and six to nine days for amputees.

Adapting classification algorithms have been proposed [Jain et al, 2012; Sensinger et al, 2009; Amsuss et al, 2014] to mitigate performance reduction. A self-correcting Artificial Neural Network (ANN) [Amsuss et al, 2014] was tested on seven able-bodied and four amputee subjects, performed almost 4.8-31.6% better than different variants of Linear Discriminant Analysis (LDA) to estimate the misclassifications contributed from active classes on five consecutive days. The above-cited non-acute studies have focused mainly on within-day performances, thus giving less attention to between days analysis. In this study, a systematic analysis is carried out within and between days classification using all pairs up to seven days to quantify the effect of time. Despite the low number of studies, there is an indication that when using surface EMG (sEMG), day-to-day performance is optimized by daily training and if not, the elapsed time since training has an effect on performance. The remaining question is whether classification based on intramuscular EMG (iEMG) or its combination (cEMG) with surface, is affected by time in a similar degree as sEMG.

The study of invasive recordings is justified by several advantages over sEMG. An intramuscular electrode can acquire signals from small and deep muscles providing localized information and thereby greatly increasing the information to control a prosthetic device. Intramuscular EMG recordings also have limited crosstalk and less affected by e.g. skin impedance, but the pickup area is small [Kamavuako et al, 2013a]. Nevertheless, besides early attempts using direct control [Herberts et al,1968; Herberts et al 1973], recent PR studies on intramuscular EMG are short-term [Kamavuako et al, 2014; Kamavuako et al, 2013b; Smith et al; 2013]. The aim of this study was to quantify the effect of time on within and between day's classification of hand motions from sEMG, iEMG and their combination (cEMG). The use of cEMG is justified by a potential hybrid system where deep muscles can contribute to enhancing performance as previously demonstrated for real-time control [Kamavuako et al, 2014].

II. METHODS

A. Subjects

The experiment was conducted on eight amputees having a transradial amputation at different levels (all males, age range: 20-56 yrs., mean age 26.56 yrs., Table 1) and 10 able-bodied subjects (all male, age range: 18-38 yrs., mean age 24.6 yrs.). All amputees were admitted to a hospital for seven days, in view of early recognition and management of possible infection that might be caused by intramuscular electrodes. Able-bodied subjects were also kept under constant observation but not admitted to a hospital. Out of the eight inducted amputees, two left the experiment (after first and third day) before the completion of data collection due to personal commitments. It should be noted that only one amputee (Amp3 Table 1) was using a body-powered prostheses, the others had never used a prosthesis. The procedures were in accordance with the Declaration of Helsinki and approved by the local ethical committee of Riphah International University (approval no: ref# Riphah/RCRS/REC/000121/20012016).

Subjects provided written informed consent prior to the experimental procedures. Normally-limbed subjects had no history of upper extremity deformity or other musculoskeletal disorders. Each amputee subject received a body-powered prosthetic hand as compensation for his participation. Normally-limbed subjects received financial compensation.

[Table 1 about here]

B. Data collection

For normally-limbed subjects, six bipolar Ag/AgCl electrodes (Ambu WhiteSensor 0415M) were used to record sEMG concurrently from the following muscles: extensor carpi radialis, extensor digitorum muscle, extensor carpi ulnaris, flexor carpi radialis, palmaris longus and flexor digitorum superficialis. For amputee subjects, depending on the size of the residual limb, five to six surface bipolar electrodes (Ambu WhiteSensor 0415) were placed at equal distance from each other around the circumference of forearm, over the belly of the muscle approximately three centimetres distal to the elbow crease and the olecranon process of the ulna. A reference electrode was placed close to the carpus of the opposite hand.

The iEMG was recorded concurrently with sEMG, using three to six bipolar wire electrodes. These were inserted to reside underneath each sEMG electrode pair so that they would measure similar activity as the sEMG. Intramuscular wire electrodes were made of Teflon-coated stainless steel (A-M Systems, Carlsborg WA diameter 50μm) and were inserted into each muscle with a sterilized 25-gauge hypodermic needle. The insulated wires were cut to expose 3mm of wire from the tip [Kamavuako et al, 2014]. The needle was inserted to a depth of approximately 10-15 millimetres below the muscle fascia and then removed to leave the wire electrodes inside the muscle. Muscle identification and electrode position were confirmed using an ultrasound scanner. All electrodes used were sterile to minimize the risk of infection. Unpacking the needle and thread took place using sterile gloves and the skin was carefully cleaned with alcohol before the needle was inserted. Intramuscular electrodes were kept in the body for the duration of the experiment (seven days) while sEMG electrodes were placed on a daily basis on the same location.

After the electrodes had been inserted, a sterile bandage was placed to cover all the insertion sites and only the tips of the wires were left outside the bandage to allow connection to the amplifiers. After each session, a second bandage was placed to cover the wires before the subject could leave the room. With this double bandage strategy, only the top bandage had to be removed for wire connections at the next session. The bottom bandage was only removed after the completion of all sessions or if the subject wished to withdraw from the experiment. No side effects or infections were reported in the study.

EMG signals were amplified (AnEMG12, OT Bioellectronica, Torino, Italy), analog bandpass filtered (10 – 500 Hz for sEMG and 100 – 900 Hz for iEMG), and sampled at 8 kHz (16-bit NI-DAQ PCI-6221). Intramuscular and sEMG electrodes placed on one of the amputees is shown in Figure 1.

[Figure 1 about here]

C. *Experimental procedures*

Subjects executed six active motions (hand open, hand close, wrist flexion, wrist extension, forearm pronation, forearm supination) and resting state (no motion). In each experimental session, data of four repetitions of five-second contractions were collected for each motion, during which subjects were asked to ramp to a medium level contraction (from rest to motion and held for three seconds) prompted by the image of the selected motion using BioPatRec [Oritz-Catalan et al, 2014], an open source acquisition software for pattern recognition. The break time between each sustained contraction was five seconds. A single repetition constitutes the execution of the seven classes in a randomized order. Five to ten-minute break was given between two repetitions to minimize muscle fatigue at the discretion of the subject. The time interval between two experimental sessions on consecutive days was approximately 24 hours. After the experimental sessions on each day, positions of surface electrodes were marked for the correct placement of electrodes on the next day. Experimental sessions were recorded for seven consecutive days. At the end of day 7, for all participants 2 - 6 (median = 5) intramuscular electrodes remained functional out of the 3 – 6 (median = 6) initially implanted.

D. *Signal processing*

Surface EMG signals were digitally high-pass filtered (third order Butterworth filtered) with a cut-off frequency of 20 Hz as well as low pass filtered with a cut-off frequency of 500 Hz. A notch filter at 50 Hz was used to reduce power line interference. Intramuscular EMG signals were high-pass filtered (third-order Butterworth filtered) with a cut-off frequency of 60 Hz and low-pass filtered with a cut-off frequency of 1500 Hz. From every five seconds of contraction time, the first second was designated as the onset phase and the last second as offset phase to avoid non-stationarity. Subsequently, three seconds of the steady-state phase per repetition were used for the extraction of features. Seven time-domain features were extracted from incrementing (by 35 ms) windows of 160 ms duration. These features were mean absolute value (MAV), zero crossings (ZC), slope sign changes (SSC), Willison amplitude (WAMP), Waveform length (WL), myopulse rate (MYOP), and cardinality (CARD). A description of these features with mathematical formulas is shown in Table 2. For ZC and SSC, no threshold was used as recommended by Kamavuako et al (2016) and a low threshold corresponding to 0.01 times the root mean square of the signal during rest was applied to WAMP, MYOP, and CARD.

[Table 2 around here]

Classification error (the ratio of misclassified decisions and total decisions) was used as the performance index. Within-day classification error (WCE) was defined as the classification obtained when training and testing data from the same day. Four-fold cross-validation was used to compute WCE where each fold corresponded to one of the four repetitions of each movement. To investigate the long-term effects on classification performance, classification between days was computed amongst the seven days of data collection. Between-day classification error (BCE) was defined as the classification error obtained when training and testing data from two different days. $Error_{ij}$ was obtained by training data on day *i* and testing on day *j*. The analysis was carried out on each EMG type (sEMG, iEMG and cEMG) for all pairs of the seven days. To quantify the effect of time, linear trend was quantified between WCE and day (1 to 7) and between BCE and day difference (Df = 1 to 6) respectively.

To reduce the dimension of the feature space, feature projection was performed using principal components analysis (PCA) which produces an uncorrelated feature set by projecting the data onto the eigenvectors of the covariance matrix [Englehart et al, 1999]. The number of PCA components was determined as those that retained 99 % variance of the original feature space. LDA was used as pattern recognition algorithm in the study due to its simplicity and the fact that its performance is similar to more complex classification algorithms such as SVM and MLP-NN [Kaufman et al. 2010].

To ensure a fair assessment of WCE and BCE, all analyses for each subject were performed using only those of intramuscular channels which functioned properly until the end of day 7. As iEMG wire electrodes resided underneath each sEMG electrode pair, the number of surface channels was reduced accordingly on a per subject basis to allow a fair comparison.

E. *Statistical Analysis*

A two-way repeated measure analysis of variance (ANOVA), with the factors EMG type (3 levels; sEMG, iEMG, and cEMG) and day (seven levels; day 1 – 7) was used to assess WCE. P-value <0.05 was considered significant and we applied the Bonferroni correction for pairwise comparison. Results are presented as mean ± standard deviation. The slope of the first order polynomial (linear regression) between WCE-day and BCE-Df was considered significantly different from zero if the 95% confidence interval (CI) did not contain zero.

III. RESULTS

Figure 2 shows the raw EMG data from both surface and intramuscular electrodes for one representative subject. Channels 1 to 6 represent raw EMG signals from surface electrodes and channels 7 to 12 represent raw EMG signals from intramuscular wire electrodes. Variations in amplitudes were observed in almost all motions, even after concatenating transient parts of the contractions (onset and offset). For the same motions, a variable activation level was observed from the same muscles. As intramuscular wire electrodes resided underneath each sEMG electrode pair, similar EMG patterns were observed from intramuscular electrodes.

[Figure 2 about here]

A. *Within-day classification*

1) *Amputees*

WCE for amputees are summarized in Figure 3. Two-way ANOVA showed that across days, each type (sEMG (12.3 ± 2.3%), iEMG (18.0 ± 1.7%), cEMG (8.5 ± 1.93%) was significantly different (P < 0.001) from each other. Performance improved over time as significant difference was found between days (P = 0.02). A standard linear regression analysis was performed on each type for the identification of time effect (days) on classification accuracies (WCE). For sEMG significant regression equation was found F (1, 4) = 14.71, P = 0.018, 95 % CI [-0.92, -0.15] with an $R^2(sEMG)$ = 0.79. Classification error reduced 0.79% per day on average. For iEMG, regression showed decay of 0.16% per day but not significant with F (1 ,5) = 0,91, P = 0.38, R^2 *(iEMG)* = 0.16, 95% CI [-1.17, 0.43]. Similarly, in cEMG, regression equation was not significant with F (1 ,5) = 4.28, P = 0.09, R^2 *(cEMG)* = 0.46, 95% CI [-1.36, 0.14]. Performance of WCE of each amputee is shown in Table 2 to indicate the inter-subject difference with clear overall increase in performance from Day1 to Day7.

[Figure 3 about here]

[Table 3 about here]

2) Correlation between residual limb vs WCE

A relationship between length of residual limbs and WCE was found by applying linear regression model between classification error and length of residual limbs (Figure 4). For sEMG regression equation was not significant F (1, 4) = .14, P = 0.73, 95 % CI [-1.1, 0.81] with an $R^2(semg)$ = 0.04. For iEMG, regression equation was found significant with F (1 ,5) = 58.71, P = 0.001, R^2 *(imeg)* = 0.94, 95% CI [-1.74, -0.82]. Similarly, in cEMG, regression equation was found significant with F (1 ,4) = 11.84, P = 0.002, R^2 *(cemg)* = 0.75, 95% CI [-0.851, -0.09]. For intramuscular and cEMG, performance in amputees was directly proportion to the size of residual limb. Amputees with shorter residual limb (7, 9 and 11 cm) reported higher error with intramuscular electrodes.

[Figure 4 about here]

3) Normally-limbed subjects

WCE for able-bodied subjects is summarized in Figure 5. Two-way ANOVA showed that across days, iEMG (8.3 ± 1.6%) was significantly different (P < 0.001) from sEMG (3.5 ± 0.96 %) and Combined (2.2 ± 0.3 %). No significance (P = 0.14) was found between sEMG and cEMG. WCE reduced over time for each type, but no significant difference was found between days (P = 0.96).

Linear regression analyses were performed on each type for the identification of time effect (days) on classification accuracies (WCE) on able-bodied subjects. None of the EMG type showed significant slope implying that WCE performance may be considered similar for each day.

[Figure 5 about here]

B. Between-day classification

BCE was computed from Df = 0 (training and testing of classifier on the same day) to Df=6 (training on day one and testing on day 7) i.e. difference between training and testing day was increased from 0 days to 6 days. Figure 6 shows the regression fit between BCE and Df (0-6) for EMG (surface and intramuscular) in amputee and able-bodied. The slopes with amputees were 3.6, 95% CI [0.42, 1.04] and 4.6, 95% CI [0.69, 1.16] for sEMG and iEMG respectively. The slopes for able-bodied were 1.55, 95% CI [-0.02, 0.64] and 4.3, 95% CI [0.26, 1.45] for sEMG and iEMG respectively. The slopes for cEMG were 1.91, 95% CI [-0.06, 0.82] and 1.59, 95% CI [0.14, 0.48] for amputees and able-bodied respectively. Results indicated that performance continuously degraded as time difference between training and testing day increased.

[Figure 6 about here]

IV. DISCUSSION

The aim of this study was to investigate the effect of time on classification using surface, intramuscular and their combination in able-bodied and amputee subjects. The analysis was performed separately for within and between days respectively. Results have indicated that subjects with upper limb amputation can learn to produce discriminative contractions which improve on successive days of training and testing. For amputees, iEMG and sEMG performance (WCE) was statistically different. For cEMG with amputees the average WCE was (12.6 ± 6.4 %) on the first day, and reduced to (7.9 ± 4.8 %) on the seventh day. A similar trend of improvement was observed in sEMG and iEMG. Although sEMG in amputees showed a significant slope between WCE and days, the average over all subjects indicates otherwise. This implies that with daily calibration, daily performance remains the same. This is contrary to our expectation where we believed that with time iEMG should be stabilized and performed better over time. Nevertheless, seven days might not be long enough time to capture a significant change. It is worth noting that similar results were reported for WCE for sEMG only in study [He et al, 2015], on average across eleven days were (14.2 ± 6.6 %) with able-bodied subjects.

The poor performance between days has been one of the main challenges in the long-term use of pattern recognition based myoelectric prostheses. In this study, we analysed the changes in performance continuously for seven days. This implies that with time, the characteristics of EMG for the same motions becomes more and more uncorrelated leading to the need for system recalibration. We believe that short-time (3-5 seconds per motion) training is problematic because it does not capture the variabilities with which humans perform movements. A way to solve this is by encouraging concatenation of training data of hundreds of days to capture the natural variabilities in movement execution. However, with such large training size standard machine learning and features may not cope and thus we encourage the use of deep learning networks for future PR control schemes. One of the promises of deep learning is replacing handcrafted features with efficient algorithms for feature learning and hierarchical feature extraction, the so-called deep features [Yoshua et al, 2007]. Because of the large number of layers, deep learning requires a large amount of data for training all the layers with several parameters, as needed to properly generalize the learning. Such amount of data can only be obtained by gathering training data from several days while the patient is calibrating the system on daily basis. Hopefully, with time variability can be learned and no additional calibration needed.

Analysis for BCE showed a decrease in performance with time. Jiayuan et al. (2015) performed a similar analysis on two amputees, who were regular myoelectric prosthesis users. For these two amputees BCE (Df=3), was 43% on average on the first day, which reduced to 13% on the eleventh day [He et al, 2015].

The trend in improvement was similar with iEMG. This observation has an important implication on real-world myoelectric based on pattern recognition, which provides the possibility of reducing the level of system recalibration for prostheses training with time. Similar variations in BCE were observed in able-bodied subjects but with a much lower level of error rate. The relatively large change in performance with amputees as compared to normally-limbed individuals may be attributed to a more substantial learning effect, as the level of training to perform required motions, most of whom were performing the targeted contractions for the first time since amputation. Consistent improvement in the performance was observed due to a neuromotor adaptation of the amputees in the form of learning. Therefore, it is implied that changes in signal characteristics and performance were either due to the improved ability of the subjects to produce consistent EMG patterns for each movement or the natural variability as discussed above.

As this was the first time for all amputees to participate in the experiment, some subjects found it difficult to follow the instructions to perform all the motions. Amp03 performed worst in the case of iEMG WCE with 36.1 % on the first day as only two intramuscular channels were included in the analysis. Encouragingly, the error was reduced to 27.1% on the seventh day, demonstrating the ability of the user to improve with learning. Intramuscular EMG performed better than sEMG in Amp02, who was the eldest and tremoring was observed in some motions. Some amputees had considerable scar tissues making it difficult to properly insert intramuscular electrodes while still be able to attach surface electrodes. Results from intramuscular could be much better if all the inserted electrodes remained inside the muscles considering the small pickup area. The use of implantable electrodes is encouraged by recent technological advances like Ripple USA [McDonnall et al, 2017]. The inclusion of six amputees has revealed that, when using iEMG, performance is directly proportional to the size of the residual limb. This can be attributed either to the reduced number of selective independent muscle as a result of amputation, a feature that is not captured by sEMG.

We observed variations in EMG amplitude from day-to-day, which may have caused high error rates. These variations may also contribute to the potential rejections of PR based upper limb prostheses. In this study, the experimental protocol was designed to reduce the effects of factors such electrode size and inter-electrode distance for example, the electrode location on the surface was marked so that every day nearly the exact location was used for recordings. But all electrodes can never be placed with 100 % accuracy. We had no means to check the positions of the wires inside the muscles after the initial insertion and thus we cannot say for sure if intramuscular electrodes recorded exactly from the same location. Despite the wires coming out of the skin, no infection was reported during or after the experiments.

Results have shown that adaptation of each subject varies when same protocol was followed for all subjects. This difference in learning can be explained by the individual adaptation to perform motions and in case of amputee’s usage of remnant muscles in daily life. It can also be implied that an amputee who is utilizing remnant muscle has a greater capacity to learn than those with intact limbs. One fact we could measure is that the size of the residual limb has an influence on performance.

V. CONCLUSION

In the study, we quantified the effect of time on the offline classification of hand motions with surface and iEMG recordings (and their combination) over a period of seven days. The effect of time on WCE was on average not significant implying that performance may be considered similar within each day. Time effect on BCE was significant and indicating that performance continuously degrades as time difference between training and testing day increases. It should be noted that iEMG and sEMG contain complementary information which justifies improved performance when combined. Lastly, for iEMG, performance in amputees was directly proportional to the size of the residual limb.

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CAPTIONS

Figure 1. Experimental setup with six intramuscular wires. Which were inserted in flexor carpi radialis, palmaris longus muscle, flexor digitorum superficialis, extensor carpi radialis longus, extensor digitorum and extensor carpi ulnaris. **A)** Wire electrodes inserted in the targeted muscles **B)** Six pairs of Ag/AgCl surface electrodes were placed beside wire electrodes **C)** Double bandaged after each experimental session.

Figure 2. Example of EMG signals from one trial from all channels showing different contraction patterns for each motion, including hand (HO), hand close (HC), wrist flexion (WF), wrist extension (WE), forearm pronation (PR), forearm supination (SU) and rest (RT).

Figure 3. Trend in classification error for surface (sEMG), intramuscular (iEMG) and cEMG along the course of seven days in amputee subjects. Each circle represents the mean across subjects ± standard deviation (bars).

Figure 4. Classification accuracies with respect to size of residual limbs.

Figure 5. Trend in classification error for surface (sEMG), intramuscular (iEMG) and cEMG along the course of seven days in able-bodied subjects. Each circle represents the mean across subjects ± standard deviation (bars).

Figure 6. Polynomial fit between BCE and Df = 0 to 6 for surface and iEMG. Results are given as mean across subjects ± standard deviation (bars).

Figure 1

A B C

Figure 2

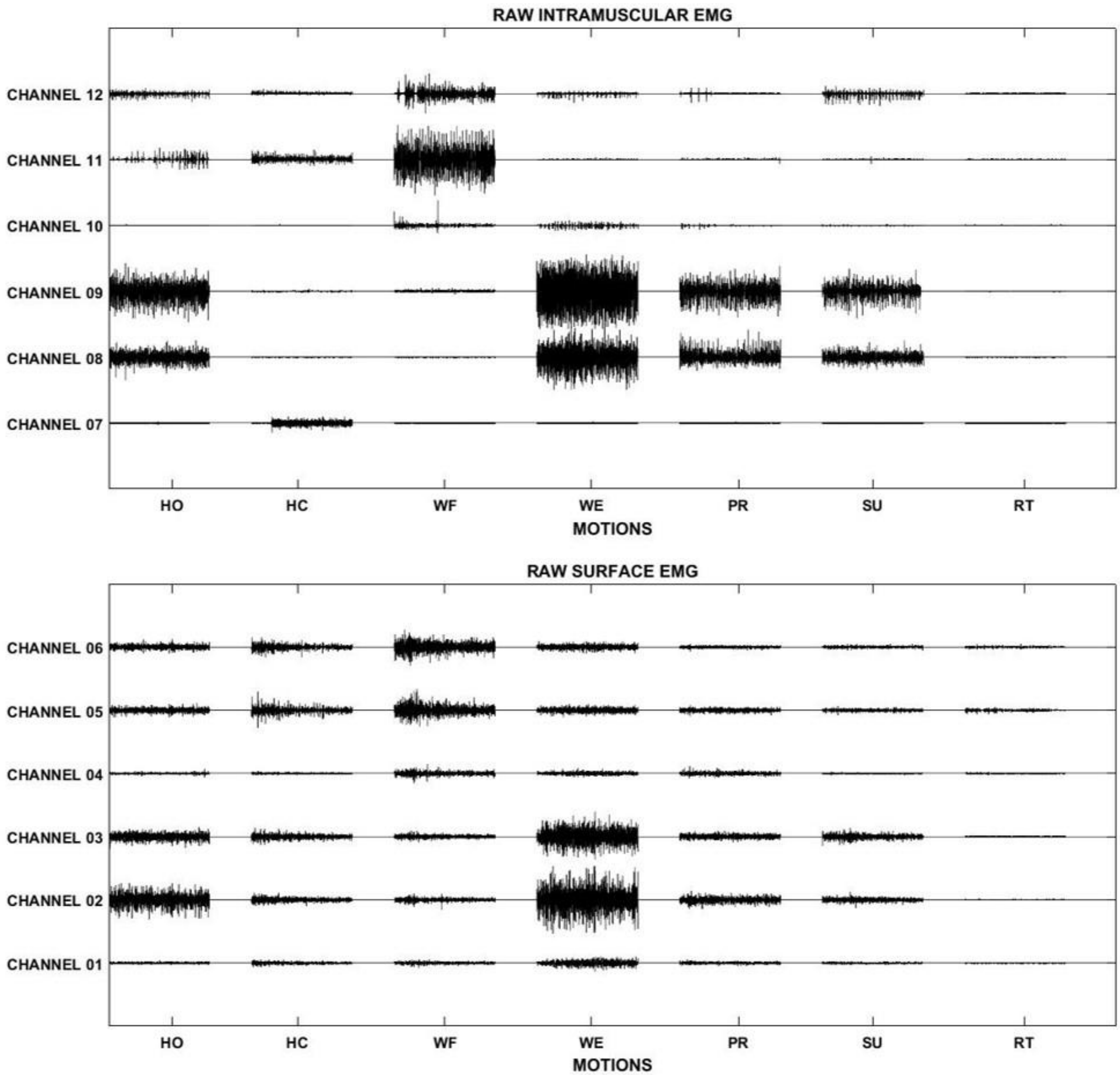
RAW INTRAMUSCULAR EMG
CHANNEL 12
CHANNEL 11
CHANNEL 10
CHANNEL 09
CHANNEL 08
CHANNEL 07
HO
HC
WF
WE
PR
SU
RT
MOTIONS
RAW SURFACE EMG
CHANNEL 06
CHANNEL 05
CHANNEL 04
CHANNEL 03
CHANNEL 02
CHANNEL 01
HO
HC
WF
WE
PR
SU
RT
MOTIONS

Figure 3

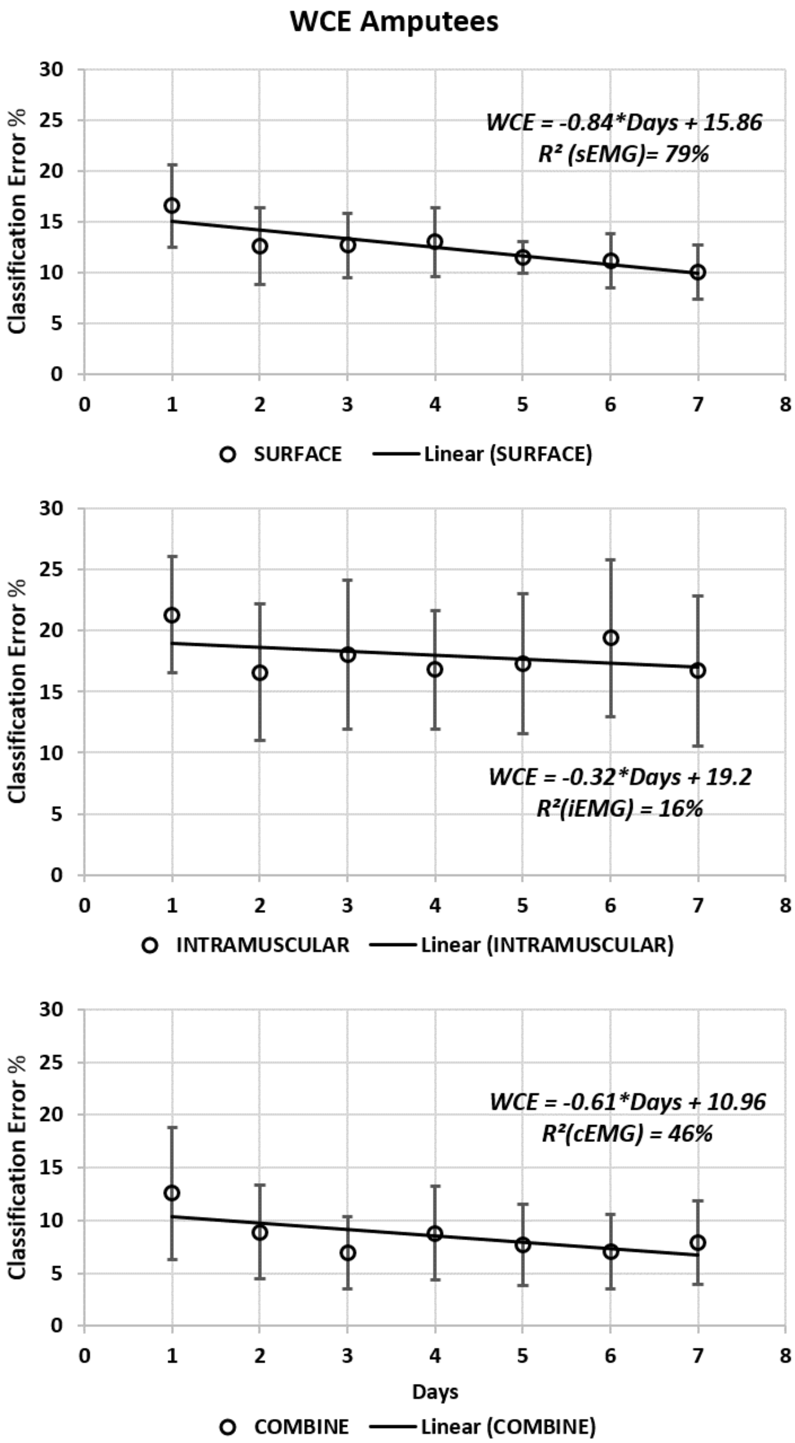
WCE Amputees
Classification Error %
WCE = -0.84*Days + 15.86
R² (sEMG)= 79%
SURFACE
Linear (SURFACE)
Classification Error %
WCE = -0.32*Days + 19.2
R²(iEMG) = 16%
INTRAMUSCULAR
Linear (INTRAMUSCULAR)
Classification Error %
WCE = -0.61*Days + 10.96
R²(cEMG) = 46%
Days
COMBINE
Linear (COMBINE)

Figure 4

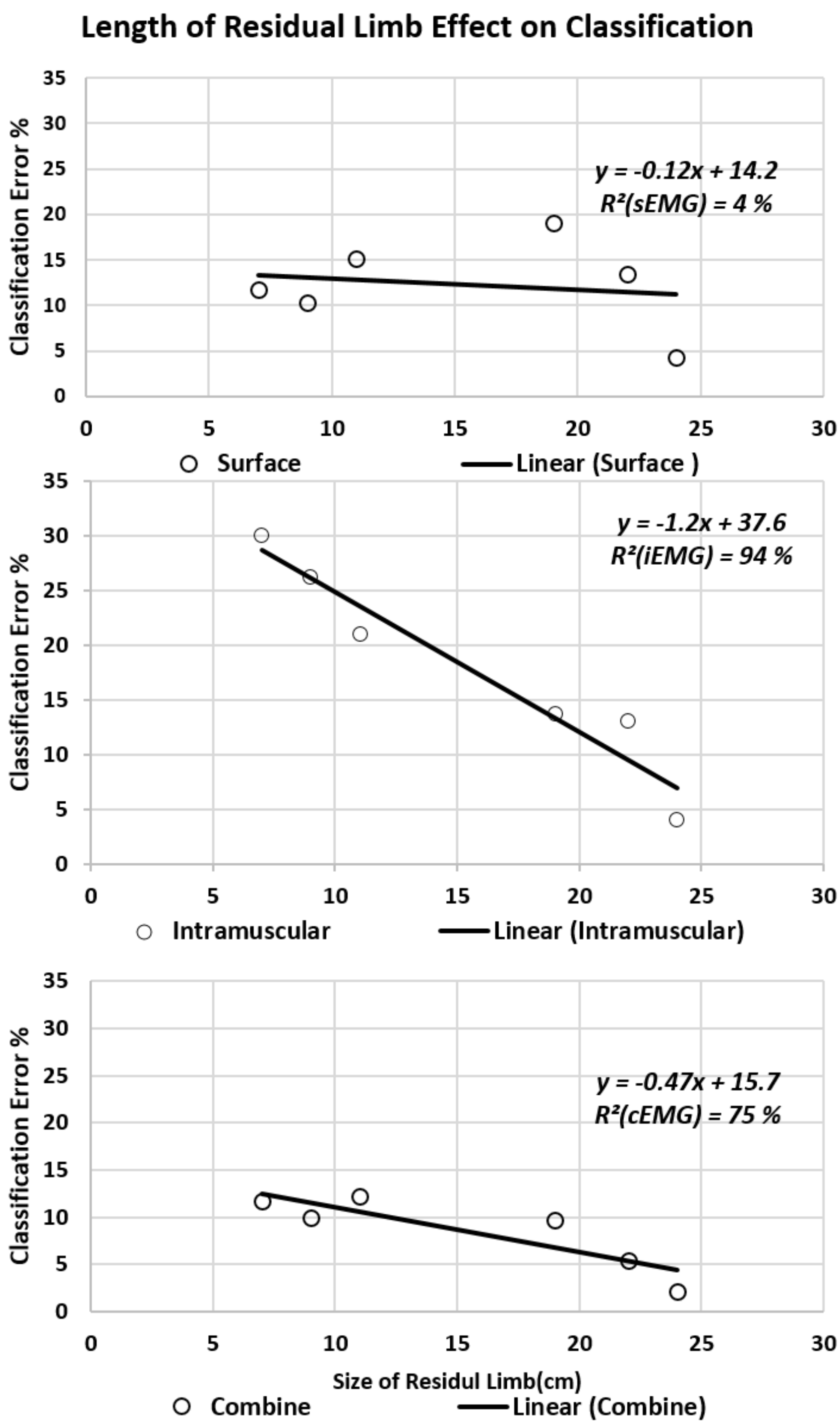
Length of Residual Limb Effect on Classification
Classification Error %
y = -0.12x + 14.2
R²(sEMG) = 4 %
Surface
Linear (Surface)
y = -1.2x + 37.6
R²(iEMG) = 94 %
Intramuscular
Linear (Intramuscular)
y = -0.47x + 15.7
R²(cEMG) = 75 %
Size of Residul Limb(cm)
Combine
Linear (Combine)

Figure 5

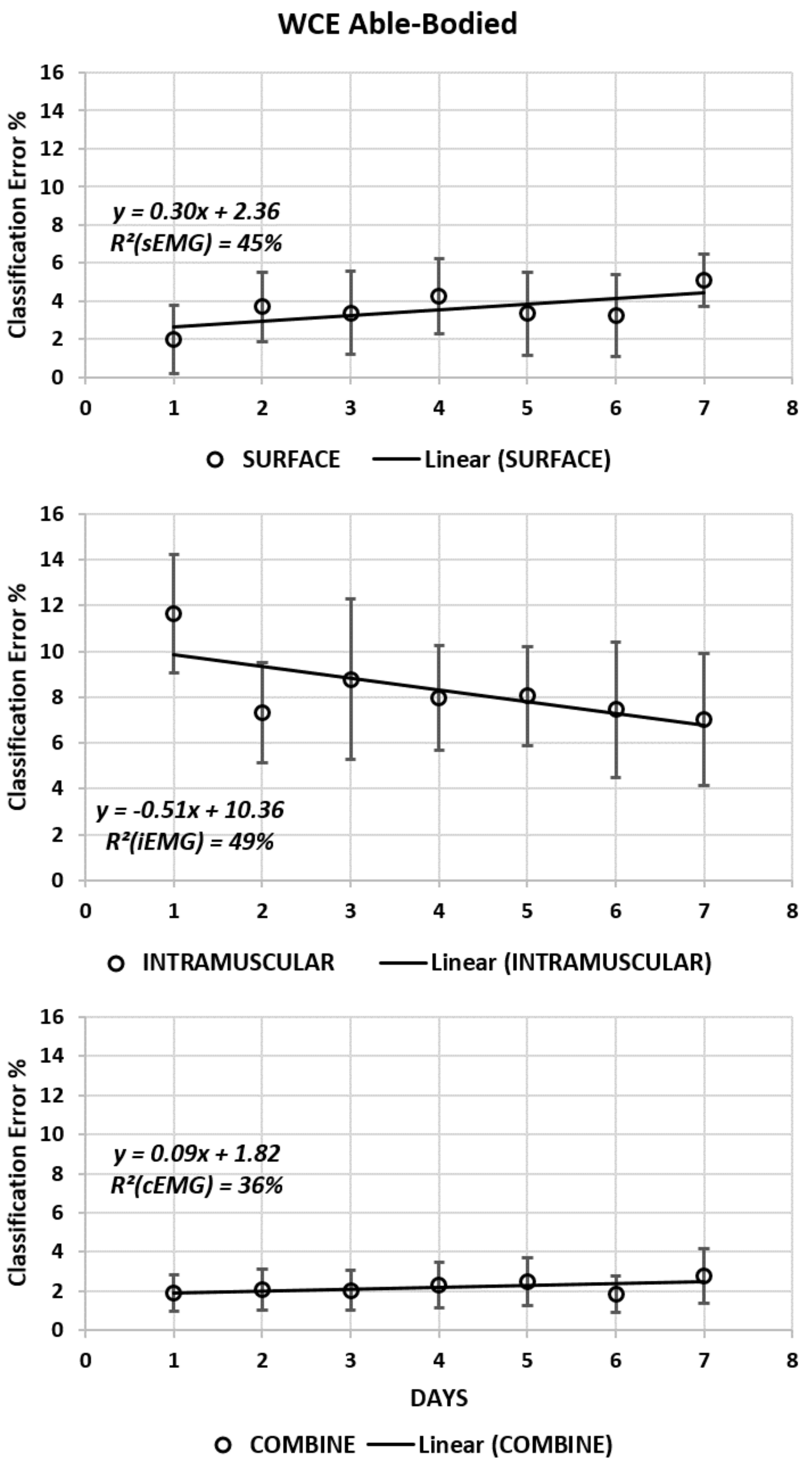
WCE Able-Bodied
Classification Error %
y = 0.30x + 2.36
R²(sEMG) = 45%
SURFACE
Linear (SURFACE)
y = -0.51x + 10.36
R²(iEMG) = 49%
INTRAMUSCULAR
Linear (INTRAMUSCULAR)
y = 0.09x + 1.82
R²(cEMG) = 36%
DAYS
COMBINE
Linear (COMBINE)

Figure 6

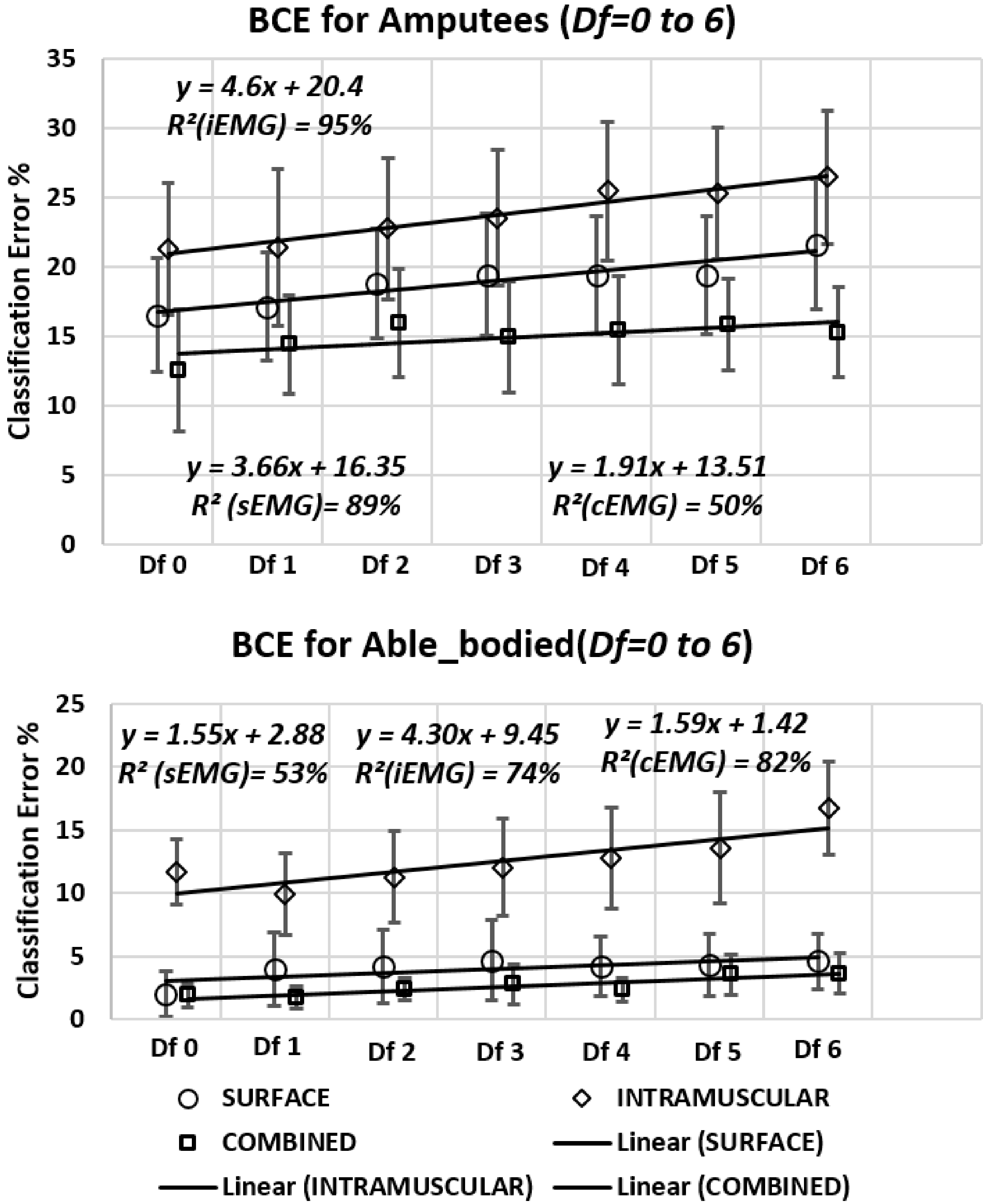
BCE for Amputees (*Df=0 to 6*)
Classification Error %
y = 4.6x + 20.4
R²(iEMG) = 95%
y = 3.66x + 16.35
R² (sEMG)= 89%
y = 1.91x + 13.51
R²(cEMG) = 50%
35
30
25
20
15
10
5
0
Df 0
Df 1
Df 2
Df 3
Df 4
Df 5
Df 6
BCE for Able_bodied(*Df=0 to 6*)
Classification Error %
y = 1.55x + 2.88
R² (sEMG)= 53%
y = 4.30x + 9.45
R²(iEMG) = 74%
y = 1.59x + 1.42
R²(cEMG) = 82%
25
20
15
10
5
0
Df 0
Df 1
Df 2
Df 3
Df 4
Df 5
Df 6
SURFACE
INTRAMUSCULAR
COMBINED
Linear (SURFACE)
Linear (INTRAMUSCULAR)
Linear (COMBINED)

Table 1. Demographic data for all amputees.

Subject	Age	Affected arm	Time since amputation	Residual forearm length
Amp1	23	Left	2 years	22 cm
Amp2	56	Right	18 years	19 cm
Amp3	31	Right	5 years	09 cm
Amp4	35	Right	2 years	11 cm
Amp5	20	Left	2 years	07 cm
Amp6	22	Right	3 years	24 cm

Table 2. Description of all features used in this study. N represents the total number of samples in a signal window; n is the sample index and ϵ is the threshold value.

Feature	Description	Formula
MAV	Mean Absolute Value (MAV) is the average of the absolute value of the EMG signal. It is an indication of muscle contraction levels.	$MAV = \frac{1}{N}\sum_{n=1}^{N}\lvert x_n\rvert$
WL	Waveform length (WL) is related to the fluctuations of a signal when the muscle is active. Thus, the feature provides combined information about the frequency, duration, and waveform amplitude of the EMG signal.	$WL = \sum_{n=1}^{N-1}\lvert x_n - x_{n+1}\rvert$
ZC	Zero Crossing (ZC) measures the number of crosses by zero of the signal and is related to the frequency content of the signal. This feature provides an approximate estimation of frequency domain properties	$ZC = \sum_{k=1}^{N-1}[(x_n \cdot x_{n+1} < 0) \cap (\lvert x_n - x_{n+1}\rvert > \epsilon)]$
SSC	Slope Sign Changes (SSC) measures the number of times the sign changes in the slope of the signal. It is another method to represent the frequency information of sEMG signal.	$SSC = \sum_{n=2}^{N-1}[(x_n - x_{n-1}) \cdot (x_n - x_{n+1})] > \epsilon$
WAMP	Wilson Amplitude (WAMP) estimates the number of active motor units, which is an indicator of the level of muscle contraction.	$WAMP = \sum_{n=1}^{N-1}\lvert x_n - x_{n+1}\rvert > \epsilon$
MYOP	Myopulse Percentage Rate (MYOP) is defined to be the average value of the myopulse output. The myopulse output is defined as one when the absolute value of a signal is above a threshold and Zero otherwise.	$MYOP = \frac{1}{N}\sum_{n=1}^{N}\lvert x_n\rvert > \epsilon$
CARD	Cardinality of a set is a measure of the number of distinct values. This can be computed in two steps. Data needs to be sorted and one sample is distinct from the next if the difference is above a predefined threshold.	Step 1: $y_n = sort(x_n), n = 1{:}N$ Step 2: $CARD = \sum_{n=1}^{N-1}\lvert y_n - y_{n+1}\rvert > \epsilon$

Table 3. Comparison of within-day classification error between surface, intramuscular and cEMG for amputee subjects. Amp 03 had only two working channels, explaining the high error rate.

	Days	01	02	03	04	05	06	07
SURFACE	Amp 01	16.5	7.8	8.5	17.3	13.1	17.7	13.2
	Amp 02	30.7	22.7	23.4	9.9	15.8	15.5	15.7
	Amp 03	16.4	7.6	10.3	11.5	7.0	9.9	9.6
	Amp 04	17.9	20.0	14.2	21.6	12.2	13.2	6.8
	Amp 05	11.6	14.1	14.3	15.5	12.0	6.8	8.3
	Amp 06	6.2	3.4	5.2	2.2	8.9	3.7	0.6
	Mean	**16.5±8.1**	**12.6±7.6**	**12.7±6.3**	**13.0±6.7**	**11.5±3.1**	**11.1±5.3**	**9.0±5.2**
INTRAMUSCULAR	Amp 01	23.7	6.4	16.7	13.1	10.4	7.1	13.9
	Amp 02	22.4	12.4	16.8	15.3	5.4	16.3	7.1
	Amp 03	36.1	30.4	15.3	17.6	25.3	31.9	27.1
	Amp 04	18.0	30.3	18.8	19.6	17.4	24.5	18.6
	Amp 05	21.0	14.7	39.2	32.6	35.7	33.8	33.4
	Amp 06	6.6	5.3	1.3	2.8	9.5	2.7	0.3
	Mean	**21.3±9.5**	**16.6±11.2**	**18.0±12.1**	**16.8±9.6**	**17.3±11.4**	**19.4±12.8**	**16.7±12.3**
COMBINE	Amp 01	8.4	3.4	3.4	5.8	5.8	2.9	8.6
	Amp 02	21.3	11.0	11.1	3.1	5.1	7.4	9.1
	Amp 03	16.1	5.3	4.3	12.5	8.7	10.6	12.2
	Amp 04	15.0	20.4	8.0	15.3	9.5	13.1	4.2
	Amp 05	11.7	10.8	14.2	14.8	9.6	8.1	12.8
	Amp 06	2.9	2.6	0.5	1.2	7.3	0.1	0.3
	Mean	**12.6±6.4**	**8.9±6.6**	**6.9±5.2**	**8.8±6.2**	**7.7±1.9**	**7.0±4.8**	**7.9±4.8**